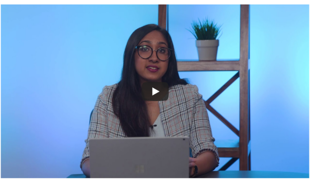
The Trade-Offs

As all things in computer science, machine learning involves certain trade-offs. Two of the most important are **bias vs. variance** and **overfitting vs. underfitting**.



Bias vs. Variance

Bias measures how *inaccurate* the model prediction is in comparison with the true output. It is due to *erroneous assumptions* made in the machine learning process to simplify the model and make the target function easier to learn. High model complexity tends to have a low bias.

Variance measures how much the target function will *change* if different training data is used. Variance can be caused by modeling the *random noise* in the training data. High model complexity tends to have a high variance.

As a general trend, parametric and linear algorithms often have high bias and low variance, whereas non-parametric and non-linear algorithms often have low bias and high variance

Overfitting vs. Underfitting

Overfitting refers to the situation in which models fit the training data very well, but fail to generalize to new data.

Underfitting refers to the situation in which models neither fit the training data nor generalize to new data.

QUESTION 1 OF 4

Here are the main terms we just discussed. See if you can match each of them with its description.

Submit to check your answer choices!

DESCRIPTION	TERM
Error that occurs when the model is too sensitive to the training data (thus giving different estimates when given new training data)	Variance
Modeling the training data well, but not generalizing well to new data	Overfitting
failing to model the training data *and* failing to generalize to new data	Underfitting
Error that results from inaccurate assumptions in model training (that are made to simplify the training process)	Bias

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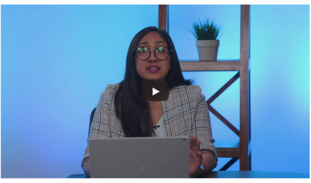

Bias vs. Variance Trade-off

The **prediction error** can be viewed as the sum of *model error* (error coming from the model) and the *irreducible error* (coming from data collection).

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prediction error = Bias error + variance + error + irreducible error
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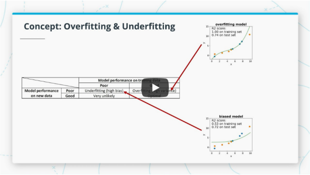
Low bias means *fewer* assumptions about the target function. Some examples of algorithms with low bias are KNN and decision trees. Having fewer assumptions can help generalize relevant relations between features and target outputs. In contrast, *high bias* means *more* assumptions about the target function. Linear regression would be a good example (e.g., it assumes a linear relationship). Having more assumptions can potentially miss important relations between features and outputs and cause *underfitting*.

Low variance indicates changes in training data would result in similar target functions. For example, linear regression usually has a low variance. *High variance* indicates changes in training data would result in very different target functions. For example, support vector machines usually have a high variance. High variance suggests that the algorithm learns the random noise instead of the output and causes *overfitting*.

Generally, increasing model complexity would decrease bias error since the model has more capacity to learn from the training data. But the variance error would increase if the model complexity increases, as the model may begin to learn from noise in the training data.

The goal of training machine learning models is to achieve *low bias and low variance*. The **optimal model complexity** is where bias error crosses with variance error.



Overfitting vs. Underfitting

- **k-fold cross-validation**: it split the initial training data into k subsets and train the model k times. In each training, it uses one subset as the testing data and the rest as training data.
- hold back a **validation dataset** from the initial training data to estimatete how well the model generalizes on new data.
- **simplify** the model. For example, using fewer layers or less neurons to make the neural network smaller.
- use **more data**.
- **reduce dimensionality** in training data such as PCA: it projects training data into a smaller dimension to decrease the model complexity.
- **Stop the training early** when the performance on the testing dataset has not improved after a number of training iterations.

QUESTION 2 OF 4

In machine learning, we often refer to a model as being overfitted when...

- [x] It is learning the training data too well at the expense of not generalizing well to new data.
- [ ] It highly simplifies assumptions on the target function.
- [ ] It has a high variance.

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QUESTION 3 OF 4

Which one of the statements is true about bias and variance.

- [ ] High bias suggests fewer assumptions on the target function.
- [ ] Low variance can cause overfitting.
- [x] Increased model complexity generally increases variance.
- [ ] Variance is due to erroneous assumptions on the target function.

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QUESTION 4 OF 4

Which technique can be used to reduce overfitting?

(Select all that apply.)

- [x] Have a validation dataset
- [ ] Have less data
- [x] Use k-fold cross-validation
- [x] Use PCA
- [ ] Stop the training when performance on training data is stable

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